ISSN 1330-3651 (Print), ISSN 1848-6339 (Online)
Received: 4 May 2025; Accepted: 13 July 2025

https://doi.org/10.17559/TV-20250504002642
Original scientific paper

Improving the Secondary Users' Quality of Service in Cognitive Radio Networks Using Partial Order Transfer Learning through Unused Channel Allocation

VIJAYAKUMAR K.*, SUMATHY V.

Abstract: Unused channel sensing and allocation in Cognitive Radio Networks (CRN) are streamlined using guard intervals to enhance the Quality of Service (QoS) of secondary users (SUs). Identifying the guard interval succeeding unused channels is tedious due to multi-interference and asynchronous resource allocations. To address this problem, the article introduces a Multi-Objective Optimization Scheme (MOOS) using Partial-Order Transfer Learning (POTL). The objectives are defined as interference minimization, optimal power utilization, and maximum channel allocation. These objectives are satisfied by untying the allocated channels that are close and away from the guard interval. The guard interval without overlapping channels is identified to reduce the allocation failures by mitigating the asynchronous intervals. The partial order derivatives are responsible for verifying the asynchronous overlap between the guard and unused channel allocation intervals. From this estimation, the overlapping and non-overlapping intervals are distinguished to improve the allocation with optimal power utilization. The transfer learning opts for the selection of a precise unused channel that satisfies maximum QoS objectives during SU response intervals. The proposed optimization scheme improves the channel allocation rate by 10.13%, power utilization efficiency by 10.5%, and network throughput by 12.03% for the maximum number of secondary user variants considered.

Keywords: CRN; partial order derivatives; QoS; transfer learning; unused channel allocation

1 INTRODUCTION

Spectrum sensing and spectrum allocation are the primary constituents in maximizing the radio frequency spectrum resource utilization in Cognitive Radio Networks (CRNs) [1]. The spectrum may not be used at its full potential or lead to over-utilization at various sites. Such a problem has been solved by the CRNs, as it offers a secondary user to dynamically detect available spectrum opportunities without interfering with the primary users [2, 3]. CR networks allow easy identification of spectrum holes as some frequencies may become free at various instances [4]. The same frequency bands can be shared uninterruptedly by many users through intelligent allocation mechanisms. CRNs form an important step in the sustainability of future wireless communication systems toward optimal utilization of the available spectrum [5, 6].

The interference mitigation through optimal spectrum allocation in CRNs seriously plays a role in quality-of-service maintenance and reliable communication between the users [7]. Secondary users share with the primary users, leading to possible interference across user groups which may degrade performance in both categories [8]. Frequency bands are assigned optimally to secondary users according to their needs but with constraints of primary users. These approaches use techniques that assign spectrum use based on real-time traffic conditions and requests from different users [9, 10]. Interference mitigation can be effective only if it improves user satisfaction and hence provides strength to the overall network. With the rising requirements of wireless communication, there has been an ever-increasing need for a cooperative model of spectrum sharing [11, 12].

Hybrid machine learning (ML) techniques can be used to achieve interference mitigation and optimal spectrum allocation in CRNs. The hybrid takes ML blend models that will be simulated in dynamic parameter space based on the state of the networks [13]. Hybrid algorithms pave the way for better spectrum management algorithms embedded with smartness and revoking nature to resource utilization [14]. The contributions of the article are: (i) To propose a novel multi-objective optimization scheme using transfer learning and partial order derivatives to improve the QoS of CR secondary users.

(ii) To analyze the proposed scheme's performance using the metrics: channel interference, channel allocation rate, channel reusability, power utilization efficiency, network throughput, and allocation failure.

(iii) To verify the proposed scheme's performance using a comparative study of the above metrics with the existing FAMSRSA [21], SVM-RDA [20], and ELSTM-PRO [22] methods.

The article is organized as follows: Section 2 discusses the related works proposed by different authors with their achievements. In Section 3, the proposed MOOS using transfer learning and partial order derivatives is discussed. Section 4 briefs the metric-based comparative analysis followed by the conclusion, limitation, and future scope in Section 5.

2 BACKGROUND AND LITERATURE SURVEY

Manco et al. [15] investigated spectrum detection in cognitive radio networks with time-varying channels. The method entails running a large measurement campaign to evaluate the performance of a mean-to-square extreme eigenvalue detector. Bagadi et al. [16] presented a unique machine-learning approach for intelligent spectrum management in cognitive radio networks. The technique combines transfer actor-critic learning and Q-learning algorithms to improve spectrum efficiency in cognitive radio access networks. Mondal et al. [17] proposed a hybrid deep learning-based strategy to improve spectrum sensing in cognitive radio networks. The proposed DeepSenseNet model has good prediction accuracy, precision, and recall. Balakumar et al. [18] proposed blockchain-based cooperative spectrum sensing for fifth-generation cognitive radio networks. The method investigates cooperative non-orthogonal multiple access to increase spectrum efficiency in these networks. To address energy constraints in health monitoring applications, Tang et al. [19] developed a mathematical model for resource allocation. The proposed method significantly improves real-time monitoring in sensor networks by combining polynomial approximation and quantum particle swarm optimization. Srivastava et al. [20] improved performance in clustering cooperative spectrum sensing for cognitive radio networks using a metaheuristic approach. The hybrid support vector machine with the Red Deer Algorithm improves detection probability while reducing error rates. To address spectrum allocation difficulties in cognitive radio networks, Gopalan et al. [21] examined techniques that employ Nash equilibrium and a multiple scheduling resource selection mechanism. The technology makes use of a fuzzy ant colony optimization-based algorithm for effective spectrum sharing. Saranya et al. [22] improved energy efficiency in cognitive radio networks using a deep learning-based optimization approach. The approach makes use of an Enhanced Long Short-Term Memory model optimized by the Red Panda Optimization algorithm.

3 PROPOSED MULTI-OBJECTIVE OPTIMIZATION SCHEME (MOOS) USING PARTIAL-ORDER TRANSFER LEARNING (POTL)

In a cognitive radio network, two access unused channels are performed under the base station such as primary and secondary users. Here, the channel allocation is based on the free channel detection where it takes place on the regular time interval. On this basis, the interferences on the channel must be reduced and for this, MOOS using partial order transfer learning is proposed. The network model with the POTL process is illustrated in Fig. 1.

The initial step is to find the spectrum handoffs and interferences managements and it is equated in the below equation as follows.

$$\begin{aligned} \nabla = & \sum\nolimits_{py}^{Sc}(S_0+i_e)*\left\{\left(Q'+n_c\right)+\left(s_i-p_y\right)\right\}+ \\ & Bas*\sum\nolimits_{Bas}\left(s_c+p_y\right)*n_c+a_l*\left(s_0+i_e\right)* \\ & \sum\nolimits_{Q'}\left(i_e-Q'\right)*n_c+Bas \end{aligned} \tag{1}$$

Spectrum handoffs and interference management are used to transmit the signal without any latency and throughput. It works as if PU asks for the particular channel to perform the task, and then SU surrenders the channel to PU. If the process is concurrent and pervasive, then low latency and high throughput are acheived. The finding is mentioned as ∇, the secondary and primary user are symbolized as s_c and p_y, the interference is i_e. The spectrum is represented as S_0, Q' is the quality of services, and the base station is described as Bas. In this format, the channel is labelled as n_c, the allocation is a_l, and the channel sensing is s_i. The quality is maintained in the desired manner and provides a better allocation strategy for primary and secondary processes.

The interference leads to the QoS degradation and it is sorted out under the transfer learning concept. The PU performns specrtum avaialbility check, and identifies a free channel for SU.

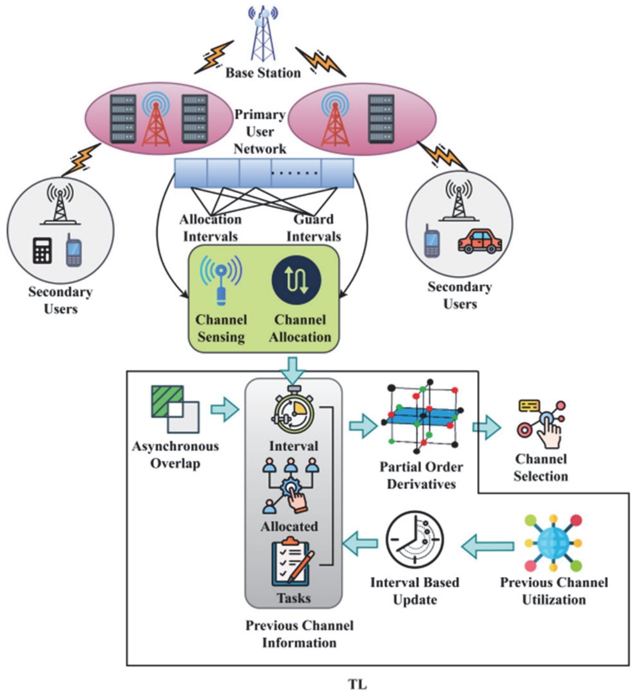


Figure 1 Network model with POTL process

The POTL process clubbed with learning and derivatives is presented in the above figure. The allocation interval, channel status, and the tasks are the input for multiple derivatives ensuring maximum allocation. The failures in channel allocation are used to update the previous utilization for careful selection. In the learning phase, the constant changes in each of the function is defined based on the available derivatives. This is recurrent using the states of the learning process. From this spectrum handoffs and interference management scheme, the uncertainty analysis is done and it is derived in the below equation.

$$\begin{aligned} Y_n = & S_0+\left|\left(a_l^2*Bas\right)\right|*p_y-v_i+ \\ & \prod\nolimits_{i_e}^{S_0} D_u-\left(b_w+l_a\right)+\left\{\begin{matrix}\left[\left(i_e+\nabla\right)*\left(a_l*Bas\right)\right]+ \\ \prod\nolimits_{s_0}\left(p_y*s_c\right)\end{matrix}\right\}* \\ & \left(b_w+l_a\right)*\nabla-a_l+\prod\left(Q'+S_0\right)*\left(p_y+s_c\right)- \\ & v_i+\left(s_0+D_u\right)-l_a \end{aligned} \tag{2}$$

The analysis is done for the uncertainty that relies on the unpredictable access to the channel allocation. This relies on two factors: latency and bandwidth and they are represented as l_a and b_w. The analysis is labelled as Y_n, the unused channel is described as D_u, and the interval of time is symbolized as v_i on this basis, the primary and secondary users are responsible for providing the allocation-based channel for the users. The interval of time is taken into consideration and gives a better allocation for the unused channel. The secondary users possess different request intervals which after the guard time are prepared for receiving response. The time required by the SU to accept its response is defined as its dedicated interval. In a conventional allocation, the request and response intervals are separated by a guard interval alone. The transfer learning is used for the finding of the uncertainty and provides a reduction of latency and bandwidth to perform the allocation and selection phase. Post to this examination is carried out for the maximization of QoS and it is discussed and formulated in equation below.

$$X_m = \frac{1}{p_y + s_c} * \sum_{v_i}^{b_w + l_a} Bas + \left(s_0 * a_l\right) + \left\{\left(Q^{'} * i_e\right) * \left(D_u + N_a\right)\right\} * s_i + \left(s_0 + \nabla\right) * Bas - D_u\left(n_c\right) + N_a - u_g \tag{3}$$

The examination is done for the QoS and it is described as X_m, the base station is used to evaluate the primary and secondary users that are used for allocation purposes. The uncertainty is considered in this case and it is labelled as N_a, where the finding is carried out for the latency and bandwidth examination, the guard interval is u_g. A guard interval is defined as the time slot between successive modulation symbols to thwart interference. In particular multipath interference and shared channel allocations utilize this guard interval concept to prevent signal degradation. The base station is used to forward the signal to the primary user where the secondary user depends on the allocation interval where the selection is done. The uncertainty occurring for v_i is computed as illustrated in Fig. 2. The n_a detection and its chances are described using the decisions presented in Fig. 2. The v_i allocated by p_y is divided into $\left(a_l | v_i\right) \forall n_c$ allocated. The allocation for s_c accommodates b_w consuming intervals to ensure maximum radio resources are allocated for i_e less communication.

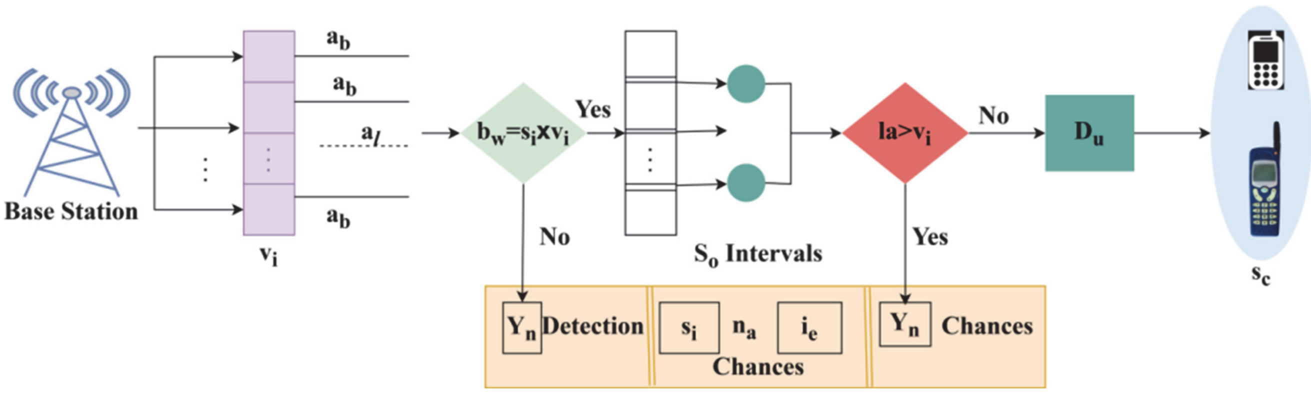


Figure 2 Uncertainty occurrence for v_i

The condition $b_w = s_i \times v_i$ ensures that ∇ is feasible for S_o intervals under separate intervals. If all the intervals are utilized by the s_c without i_e or the need for guard intervals, then D_u for $l_a = v_i$ (or) $l_a < v_i$ is identified. Such identified D_u is influenced by s_i to perform s_c communication in the consecutive interval. The l_a condition failure identifies the Y_n chances in any $a_l \in n_c$. The b_w condition failure detects the exact Y_n chance for new s_i other than i_e. Therefore, the new s_i and i_e jointly in the same v_i is defined as n_a (Fig. 2). The finding is followed for the unused channel and followed by this allocation is carried out. From this observation format, the base station uncertainty is used to indicate the allocation interval for the channel access. The uncertainty is used to find the unpredictable channel access where the base station is used to examine the secondary user $\left(s_c + Bas\right) * D_u$. From this examination step, unused channel allocation is done in the time frame manner and it is derived below.

$$D_u\left(n_c, a_l\right) = u_g - \left(b_w + l_a\right) * \sum_{u_d \in s_i}^{Q^{'}} S_0 + \left(v_i * u_d\right) \tag{4}$$

The unused channel allocation is done for the interference reduction where the bandwidth and latency are considered for the free channel detection. On this examination step of unused channel allocation, the base station is used to indicate the guard interval where the unpredicting takes place and it is represented as u_d. This encounters the QoS on the desired time interval on the spectrum-based signal processing under the primary and secondary user. From this basis, unpredicting is followed up on the spectrum-based mechanism and that illustrates the channel access $n_c\left(a_l - u_g\right) - v_i$. Thus, establishment is done regarding the channel-based forwarding among the primary and secondary users on the observation of guard interval. The guard interval is computed for throughput maximization, optimal power utilization, and maximum channel allocation. These objectives are satisfied by untying the allocated channels that are close and away from the guard interval and it is formulated in the following equation.

$$X_m\left(u_g\right) = \left(n_c + a_l\right) + \left(s_0 * Q^{'}\right) + \prod_{Q^{'} \in v_i}\left(N_a + a_l\right) + \prod_{s_i} S_0 * \left(Q^{'} + Bas\right) * a_l\left(u_d\right) \tag{5}$$

The guard intervel is examined and transfer learning is employed to improve the QoS. The analysis takes place to address the interference and improve the throughput in the cognitive radio network. The sensing is carried out for the finding of the spectrum relatively to enhance the throughput. The channel allocation is considered for the unpredictability of the radio network.

$$n_c(s_i) = \left\{(s_0 * a_l) + \sum_{D_u} (v_i + Bas)\right\} * N_a \tag{6}$$

The channel sensing is done to find the allocation interval based on the guard interval that has been estimated accurately. This channel sensing is used to allocate the primary and secondary user based on the unused channel allocation on base station $Bas + (D_u - v_i)$. This phase of spectrum allocation is carried forward with the transfer learning concept. The objectives are defined as throughput maximization, optimal power utilization, and maximum channel allocation. The assigning of task based on the channel sensing is equated in the following derivative.

$$n_c(a_l) = \begin{cases} 1 & \text{if} \prod_{i_e} S_0 + (s_i + c_k) * \partial_{f0} - v_i \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

The channel allocation is performed by frequently checking for the free channel in the network. It works on the "if and otherwise" condition where the "if" condition states whether the channel is free or not and it is represented as ∂_{f0}, the allocation of tasks is done, whereas, checking is labelled as c_k. On performing this condition basis, the channel allocation proceeded at frequent intervals. The channel sensing and allocation processes are illustrated in Fig. 3.

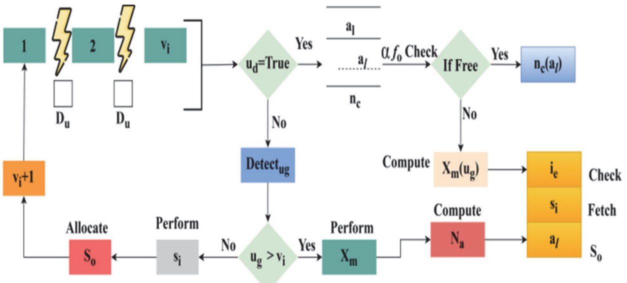


Figure 3 $n_c(s_i)$ and $n_c(a_l)$ processes

The independent processes: $n_c(a_l)$ and $n_c(s_i)$ are diagrammatically presented in Fig. 3. The v_i and D_u intervals are required to maximize the S_o allocation in $v_i \forall (a_l \in n_c)$ or $(v_i + 1)$. If the allocations are successful then l_a minimized b_w utilization becomes feasible. This allocation does not experience i_e until the overlapping between v_i and D_u is experienced. To reduce such overlapping, u_g is defined before $s_i \forall S_o$ allocation. Therefore, the chance of $(u_g \geq v_i)$ observed requires $X_m \forall Y_n$ using N_a experienced. This follows a series of i_e check, s_i fetching, and a_l for u_g less communication. Based on the allocations, the u_d identified in high l_a that surpass $(u_g \geq v_i)$ requires a pre-trained partial derivative process. From this step, the identification of guard interval succeeding unused channels is tedious due to multi-interference and asynchronous resource allocations. This is sorted out by using transfer learning along with the four parameters.

3.1 Transfer Learning Application

Transfer learning process is implied to identify the asynchronous overlapping intervals through consecutive input processing. By using the basic features of the first task the second task relates to the process and computes efficiently. The below sections are used under the transfer learning concept.

3.1.1 Pre-Trained Model

This is the preliminary step in transfer learning that has more data which has the collection of features and patterns regarding the task assigned on the cognitive radio network that indicates the guard interval. The below equation is used how the pre-trained model works for the assigned task.

$$Y_r(k_t) = p_r * (a' + s_c) * \frac{Q' + n_c}{T_y(0)} + s_i \tag{8a}$$

The analysis is done for the task assigned on the radio network, the task is represented as k_t, the assigning is labelled as a'. The pre-trained model is symbolized as p_r. From this step, the quality is maintained accurately under the transfer layer from the initial step and it is described as $T_y(0)$. The guard interval is used to state the allocation interval for the task assigning which takes place on the initial layer. This uses the pre-trained model with the previous processing techniques that give a clear idea of task computation for further tasks. The transfer learning model acts as both supervised and unsupervised based on the context where it is employed. This employment in the proposed method is unsupervised as it learns from the previous channel allocations. The $n_c(a_l)$ entities such as s_i, user count (for demand), and the interval are used to update the learning model to decide over the current state of the decisions. The decisions on pending task-based sensing and reallocations are made to improve the precise retention of guard intervals. Therefore, the aforementioned cumulative entities are used to ensure the learning network is uptodate to prevent false allocation failures.

3.1.2 Base Model

It refers to the models which have been pre-trained; it mainly focuses on the input data and follows the hierarchical illustration. The below equation formulates how the pre-trained model works for the input layer and task assigning with the guard interval.

$$b_e(\nabla) = T_y(0) + (a'(k_t) * p_r) + n_c \tag{8b}$$

The base model proposed here is to find the input data as the task where the transfer layer works accordingly on the unused channel such as it is free. The free channel allocation is followed up with the uncertainty and progresses hierarchically.

3.1.3 Transfer Layer

It holds the information of the present task and previous task with the generic information. This is performed layer by layer where it holds the information at the start of the transfer layer which is the initial layer and it is formulated in the below derivative.

$$T_y(Y_r) = (l_a + b_w) * \prod_{a'} (k_t + n_c) * u_g - s_0 \tag{8c}$$

The transfer learning is processed in layer-by-layer order with the information that is the task. Based on the unused channels, free tasks are assigned with the guard interval. This is performed on the interval slot and channel-free basis. On this execution step, the channel sensing is done with the allocation rate of the task.

3.1.4 Fine-Tuning

With the present task the retraining is carried out under the layers. This technique uses the pre-training model to modify the current task with the use of the previous trained iterations.

$$U_f = \prod_{s_c}^{a_l} (N_a + n_c) * \nabla + \left[\left(a' + k_t \right) - v_i \right] * \partial_{f0} \tag{8d}$$

The fine-tuning is carried out in the above equation, described as U_f, which uses the pre-trained model for the computation. This relies on the guard interval and examines the transfer with n number of layers. The four parameters are used to identfy the asynchronous overlapping , defined in Eq. (9).

$$A_v = n_c (s_i + a_l) * \sum_{i_e} Bas + (s_0 + s_c) * p' \tag{9}$$

The asynchronous overlapping is computed above and it is labelled as A_v; here the prediction is followed up and it is represented as p'. This step illustrates the channel-based sensing and allocation from the guard interval. The transfer learning functions are illustrated in Fig. 4. The transfer learning functions for A_v detection and partial order extraction are presented in Fig. 4. A partial order derivative is a multifaced function to satisfy the objectives defined jointly. In providing solution for one objective, the other objective variables are assumed as constants to measure the changes in the current function. The partial order derivative constants are used for separating allocation intervals, surpassed by the guard time. If the separation is successful then the consecutive allocation without overlap is performed. The inseparable channels experience an active communication for which guard intervals are to be separated. Based on the number of separable derivatives the consecutive guard interval and channel allocations can be made. This reduces the chances of allocation failures and improves the communication efficiency.

The $b_e(\nabla)$ relies on $Y_r(k_t)$ for any v_i under s_i and a_l that are equal in between D_u. If the allocated u_g overlaps D_u, then v_i experiences i_e. Therefore, this case outwits both u_d and N_a as defined in Fig. 2 and Fig. 3 processes. Thus, the base model relies on u_d and N_a proportion to define $T_y(o)$. This initialization is the $a' = 0$ (or) $' = 1 \forall n$ layer satisfying $n_c(s_i)$ and $n_c(a_l)$. If these cases are not balanced, then U_f assignment takes place. This assignment identified the chances of u_d (or) N_a provided $\partial f_o = 1$. Again, the parameters $n_c(a_l)$ and $n_c(s_i)$ are induced for c_k in the successive a' for which p_r is updated. Based on the update, the n adjustments for derivatives are defined; this ensures that i_e is confined in any v_i regardless of D_u and u_g assignment.

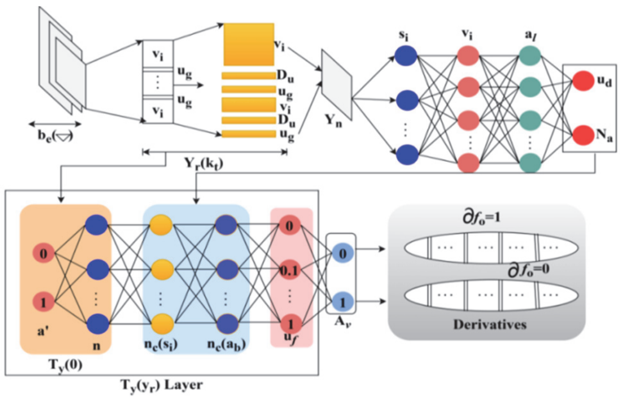


Figure 4 Transfer learning functions illustration

This representation uses the pre-trained model on transfer learning. The partial order derivative process is discussed in the following section. The asynchronous overlap interval identified using the TL process is analyzed using this derivative function for its least possible occurrence.

3.2 Partial Order Derivative

The partial order derivatives are allocated based on the allocated and unallocated channels analytically. A channel allocation from its initial to final state based on non-overlapping to shared state is used to define the partial orders. Therefore, a channel is categorized as completely free to partially occupied, to occupied (allocated). It requires a proper wait time to reverse the shared state to free/idle state. The state of the channel as busy/idle is decided based on its response and interference. If the interference is less and the response is high, then a channel is suitable to be free. Besides, this computation is not fixed as it relies on the number of SUs, tasks, and overlapping channels available. The channel must support noise reduction and admit maximum response intervals. Besides, as the derivatives cross the precise conditions (allocation) the derivatives are revisited based on any new channel.

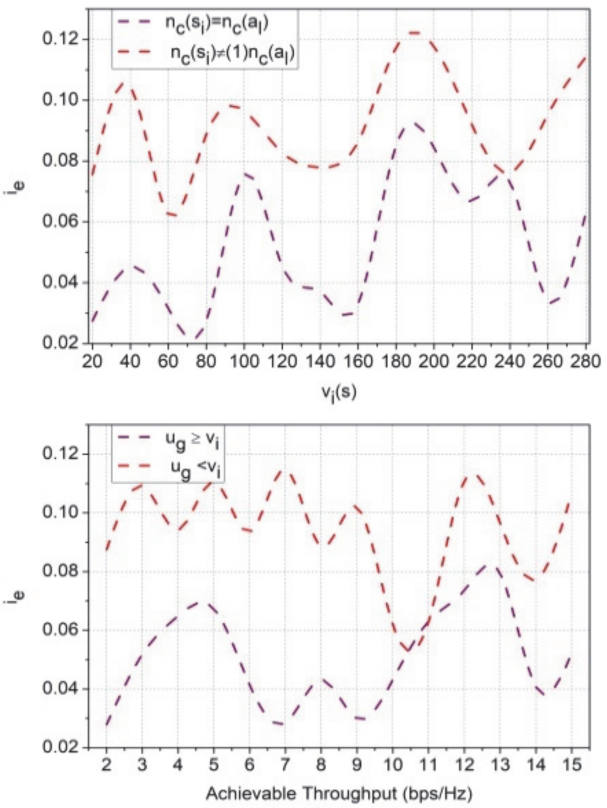
This is a cyclic process based on different user densities where allocation and releasing are continuous. It is used to find the maximum power utilization and channel allocation; it is defined as the changes that occur on the input whereas the remaining is constant. This untying is performed during the channel sensing and allocation defined at regular primary user intervals. The following equation is used for the partial order derivative processing.

$$\varphi = \frac{a_l\left(s_c + u_g\right) * Bas + c_k}{\left(N_a * n_c\right) + A_v} \tag{10}$$

The partial order derivative is expressed in Eq. (10) and it is symbolized as φ, this factor is followed up in the asynchronous manner of overlapping. Here, checking is done for the unused free channel and based on this task is forwarded. Following up this partial order derivative the channel selection for guard interval is done to improve the QoS.

$$n_c\left(S\right) = \varphi * \frac{k_t}{a_l} + A_v * \left(\partial_{f0} + D_u\right) - \left(i_e + p_r\right) * Q' \tag{11}$$

The channel selection is done to improve the QoS and it is represented as S. This uses the partial order derivative for the examination of unused channel and guard interval under the transfer learning. The proposed multi-objective optimization scheme enhances the efficiency of radio resource allocation and sharing by reducing i_e in any v_i. This multi-objective improvement based on problem constraints is analyzed in the self-parameter discussion section. Thus, in the first self-parameter analysis, i_c under different constraints is presented in Fig. 5 analysis.



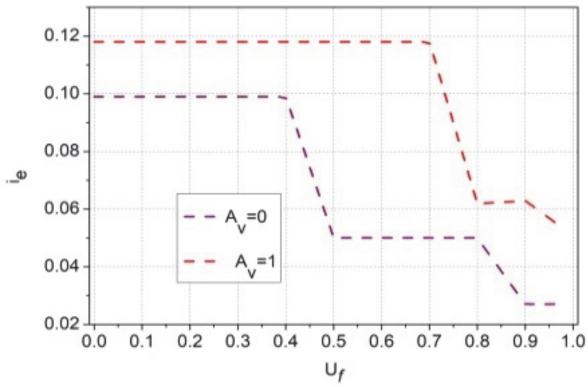


Figure 5 i_e analysis of different constraints

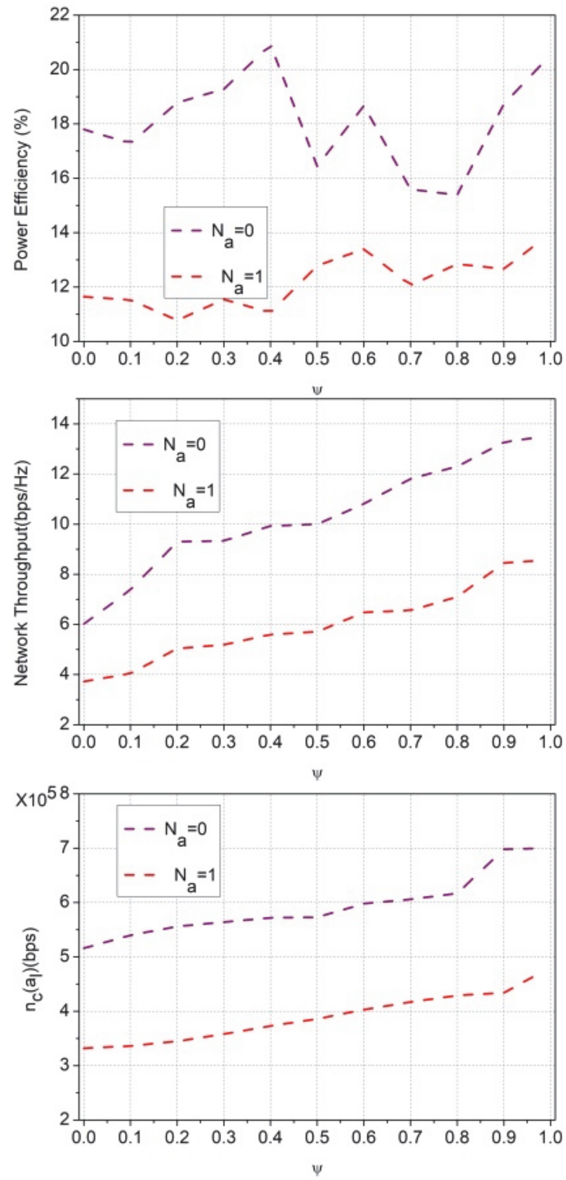


Figure 6 Power efficiency, network throughput, and $n_c(a_l)$ analysis for ψ

The constraints in which i_e is analyzed are: $n_c\left(s_i\right) = n_c\left(a_l\right), n_c\left(s_i\right) \neq n_c\left(a_l\right), \left(u_g \geq v_i\right), \left(u_g < v_i\right)$, and $\left(A_v = 1, A_v = 0\right)$. The case is obvious for v_i, achievable throughput, and U_f provided maximum $b_e\left(\nabla\right) \forall p_r$ matches with $T_y\left(o\right)$ and the derivatives. The $\partial f_o = 1$ is the training validation condition to enhance the i_e suppression. The $s_i \forall n_c$ separated by D_u are identified to maximize A_v. Therefore, a' based on U_f and ψ reduces i_e in v_i and D_u intervals (Fig. 5). Following the above analysis, the impact of ψ over power, throughput, and $n_c(a_l)$ is studied using Fig. 6 analysis.

In the above Fig. 6, the power efficiency, network throughput, and $n_c(a_l)$ analysis for increasing ψ is presented. The i_e less allocations increase the power allocation and utilization efficiency between p_y and s_c in any s_i interval. The identified i_e is suppressed using ψ balanced through U_f and A_v less $n_c(a_l)$. Therefore, the power utilization is confined to v_i and (v_i+1) intervals that are active to achieve high network throughput. Besides the N_a identified D_u or s_i intervals are substituted with u_g to temporarily present i_e. In the final case of $n_c(a_l)$, i_e fewer intervals are identified and distinguished to maximize the throughput and $n_c(s_i)$ to reduce N_a.

4 PERFORMANCE ASSESSMENT

The proposed scheme is experimentally verified using MATLAB simulations. A cognitive radio network with 1000 × 500 m^2 dimensions is considered with 4 Base stations, 11 p_y, and 40 s_c. The base station is capable of covering 500m and p_y with a 250m range. The transmit power from the base station to p_y in 55 dBm and $p_y - s_c$ transmit power is 40 dBm. The b_w allocated is 2MHy and the data rate is 1 Mbps; with s_c frequency at 2.4 GHz. Using this experimental setup the metrics of channel interference, allocation rate, reusability ratio, power utilization efficiency, network throughput, and allocation failures are analyzed. These metrics are compared with the existing FAMSRSA [21], SVM-RDA [20], and ELSTM-PRO [22] methods discussed before. The SNR (dB) is varied from –20 to +20 and the s_c from 5 to 40 in this comparative analysis.

4.1 Channel Interference

The channel interference for the proposed work is observed for the different SNR and SU. This is ensured by improving the QoS in the end-to-end network that is initialized from the base station. It is based on the allocation mechanism where the channel interferences are addressed and reduced with the use of the transfer learning concept $\left(T_y(0)+a_l\right) * \sum_{a'} k_t * v_i$. This computation takes place based on prediction with the previous step of processing. The QoS is benchmarked on this to reduce the channel interferences on the secondary user. Thus, the bandwidth and latency are related to the higher prediction rate for assigning the task to the secondary user (Fig. 7).

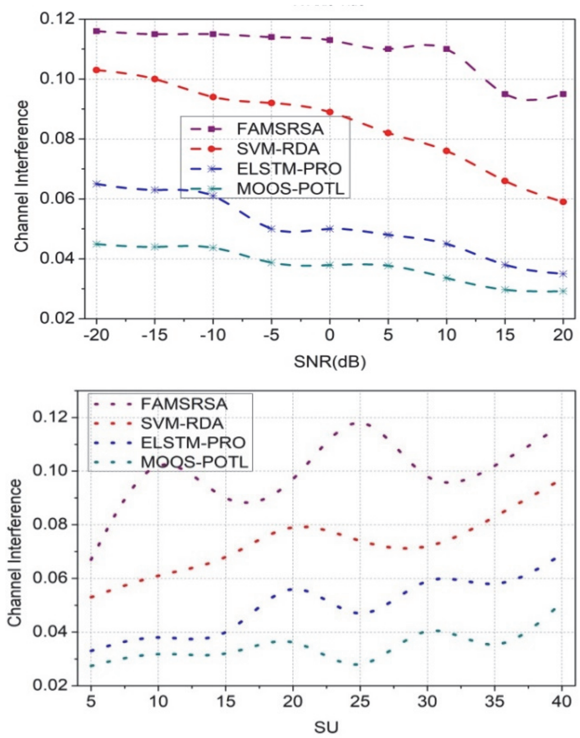


Figure 7 Channel interference

4.2 Channel Allocation

The channel allocation is high concerning the guard interval where the unused channel sensing is initiated. This ensures the channel selects and finds the overlapping $(S+n_c) * \prod_{\nabla}(s_c+a_l)$.

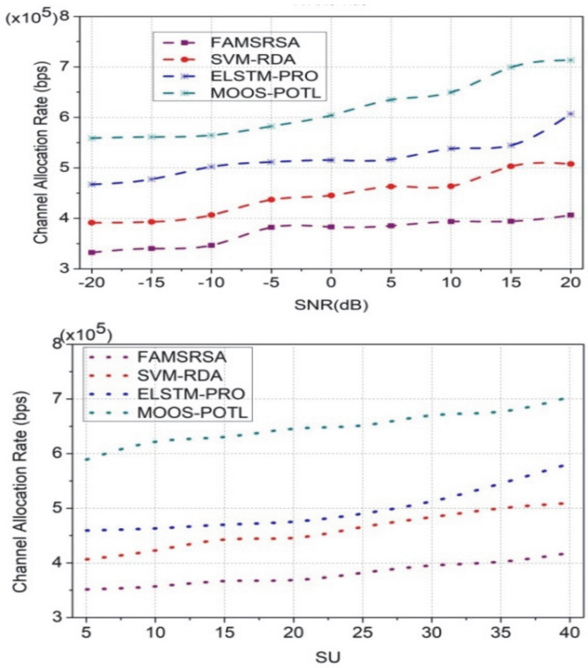


Figure 8 Channel allocation

The base station is responsible for the sensing of channels with a higher spectrum range. If the utilization factor increases, then the channel allocation also increases concerning the regular interval. The guard interval is used to define the channel selection and from this allocation is done accurately for the unused channel on the cognitive radio network. In this processing step, the channel allocation is done for the SNR and secondary user on the unused channel (Fig. 8).

4.3 Channel Reusability

In Fig. 9, the channel reusability comparisons for SNR and SU variants are presented. It shows a higher value compared to the previous methods. In this observation, the prediction and unidentified are followed up for the current and previous methods and ensure the QoS with a higher utilization factor.

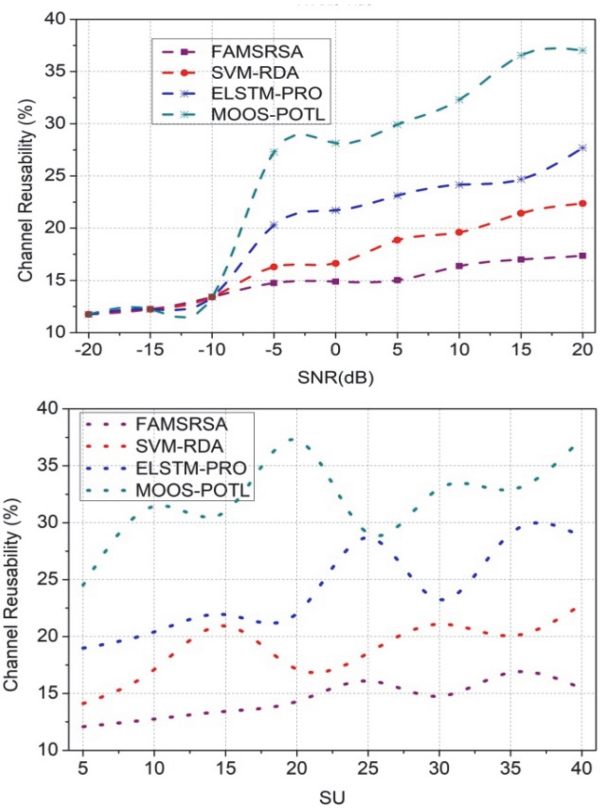


Figure 9 Channel reusability

The reusability is done for the channel-based interference detection where it is evaluated on the guard interval $u_g\left(s_c + n_c\right) - D_u$. The uncertainty is used to examine the transfer learning concept on the interval of time on the free channel. Thus the channel reusability increases for the secondary user on the allocated channel.

4.4 Power Utilization Efficiency

The power utilization efficiency is found to be for SNR and SU, exploiting balanced latency and bandwidth on the guard interval. The throughput at s_c analyses the interference by sensing the channel and identifies the uncertainty. The prediction is done with the current and the previous step of processing and it is observed in the base station $\left(Bas + s_c\right) * \prod_{l_a}\left(b_w + S_0\right)$. The overlapping is used to define the partial order derivative where the channel free and used differs whereas, allocation will remain constant $\partial_{f0} + \sum_{l_a}^{b_w}\left(Q' * N_a\right)$. Thus, the efficient utilization of the power factor is high for s_c (Fig. 10).

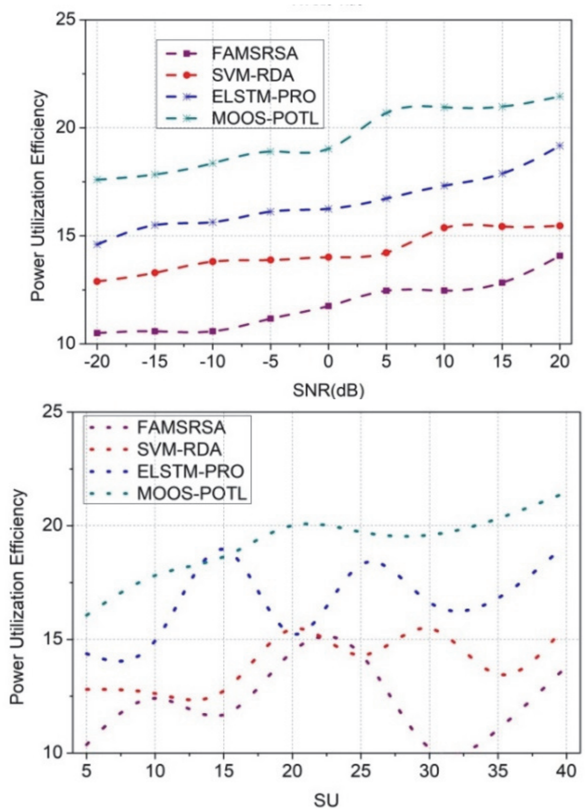
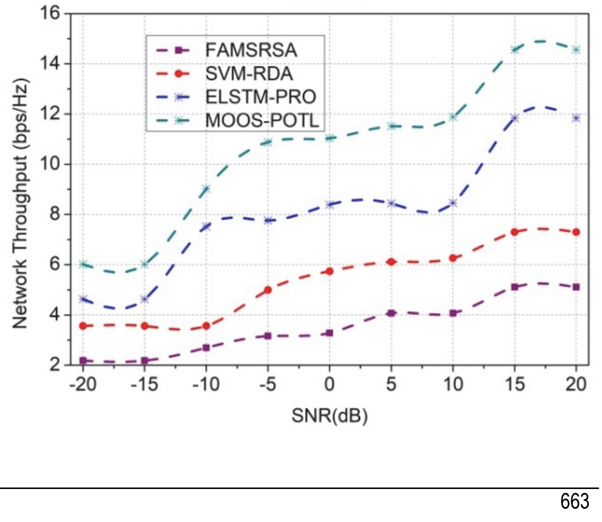


Figure 10 Power utilization efficiency

4.5 Network Throughput

The network throughput for the proposed work is high for SNR and SU. Both the latency and bandwidth are balanced to improve the network throughput on S_o allocation. This evaluation of network throughput is observed on the allocated channels which are free and unused. The free channels are associated with the spectrum-based computation $\left(S_0 + \partial_{f0}\right) * n_c + c_k - v_i$. By computing this throughput, the guard interval works on the free and unused channels and based on this power utilization decreases, maximizing the throughput for the different channels.



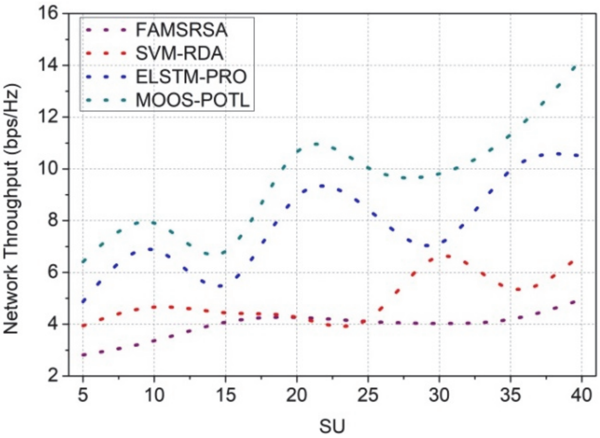


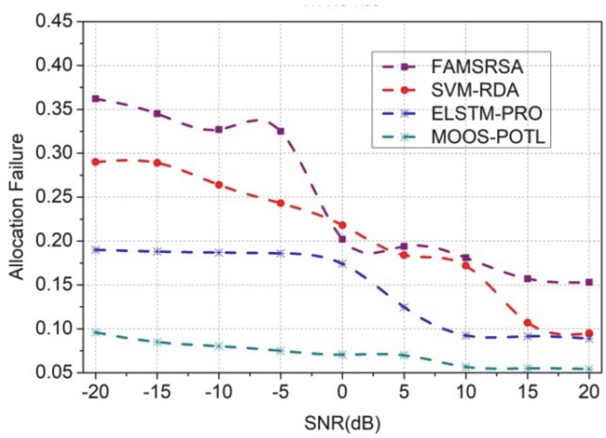
Figure 11 Network throughput

If the QoS is improved, then the throughput also increases which is directly proportional to each other. In this case, network throughput is used to define the higher channel allocation from the selected channel sensing (Fig. 11).

4.6 Allocation Failure

The allocation failure is less (Refer to Fig. 12) on allocating the guard interval for the active channel sensing. This examination step relies on the latency and bandwidth and provides better channel allocation $a_l\left(n_c+N_a\right)-\partial_{f0}$. The computation is used to state the guard interval where the throughput is used to initialize the transfer layers for identifying the channel. The task allocation is used to define the higher throughput with lesser power utilization among the resources. Based on this examination step, task allocation failure is reduced in this proposed work and balances the QoS.

The proposed optimization scheme improves channel allocation rate by 10.13%, reusability by 16.07%, power utilization efficiency by 10.5%, and network throughput by 12.03%. This scheme reduces the channel interference by 10.81% and allocation failure by 12.43% for the maximum SNR.



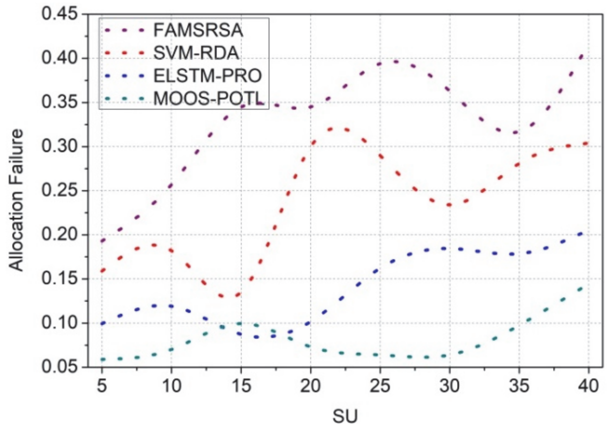


Figure 12 Allocation failure

The proposed optimization scheme improves channel allocation rate by 10.23%, reusability by 14.54%, power utilization efficiency by 10.44%, and network throughput by 11.12%. This scheme reduces the channel interference by 10.14% and allocation failure by 11.6% for the maximum SU count.

5 SUMMARY

The comparative analysis results are summarized with the findings in Tabs. 1 and 2 for the SNR and SU variants.

Table 1 Comparative analysis summary for SNR

Metrics	FAMSRSA	SVM-RDA	ELSTM-PRO	MOOS-POTL
Channel Interference	0.095	0.059	0.035	0.0292
Channel Allocation Rate / bps	4.064	5.076	6.071	7.133
Channel Reusability / %	17.36	22.37	27.699	37.015
Power Utilization Efficiency	14.08	15.46	19.17	21.456
Network Throughput / bps/Hz	5.11	7.3	11.84	14.556
Allocation Failure	0.153	0.095	0.0889	0.0543

Table 2 Comparative analysis summary for SU

Metrics	FAMSRSA	SVM-RDA	ELSTM-PRO	MOOS-POTL
Channel Interference	0.117	0.097	0.069	0.0511
Channel Allocation Rate / bps	4.183	5.095	5.819	7.0385
Channel Reusability / %	15.43	22.83	28.78	37.421
Power Utilization Efficiency	13.81	15.66	19.21	21.477
Network Throughput / bps/Hz	4.96	6.73	10.5	14.261
Allocation Failure	0.417	0.304	0.2057	0.1446

5 CONCLUSION

This article introduced the multi-objective optimization scheme using partial order transfer learning to improve the spectrum allocation features of CR networks. The proposed scheme focused on power efficiency, channel reusability, and interference reduction in the resource allocation between primary and secondary users. The learning part validated the allocation interval's existence close and away from the guard time to reduce the overlapping problem. This process is defined with a maximum QoS defining base model to a validated interval allocation ensuring maximum requirements on network throughput and interference are satisfied. As the asynchronous allocations are detached from the guard intervals, the base pre-training model is modified with the last known channel allocation rate. Thus, the proposed scheme improved the channel allocation rate by 10.23%, power utilization efficiency by 10.44%, and network throughput by 11.12% and reduced the channel interference by 10.14% for the maximum SNR.

6 REFERENCES

[1] Dappuri, B., Sikha, M. B., Venkatesh, T. G., & Sindhu, P. U. (2024). An analytical framework for cooperative cognitive radio network for spectrum leasingsharing. *Physical Communication*, *66*, 102464. https://doi.org/10.1016/j.phycom.2024.102464

[2] Govindasamy, S., Ramudu, K., Suriyakrishnaan, K., Thouti, S., Tiwari, M., Tanguturi, R. C., & Singh, M. (2024). MULTI-TASK crow swarm-intelligent algorithm for enhancing spectrum efficiency and energy conservation in cognitive radio ad-hoc networking. *Measurement: Sensors*, *33*, 101181. https://doi.org/10.1016/j.measen.2024.101181

[3] Giri, M. K. & Majumder, S. (2023). Extreme learning machine based identification of malicious users for secure cooperative spectrum sensing in cognitive radio networks. *Wireless Personal Communications*, *130*(3), 1993-2012. https://doi.org/10.1007/s11277-023-10368-6

[4] Kishore, K. K., Rajasekaran, A. S., Keshta, I., Byeon, H., Bhatt, M. W., Irshad, A., & Ofori, I. (2024). Intelligent dynamic spectrum access using fuzzy logic in cognitive radio networks. *Discover Applied Sciences*, *6*(1), 18. https://doi.org/10.1007/s42452-024-05641-7

[5] Zhang, Y., & Wang, J. (2023). Effectiveness, fairness and social welfare maximization: service rules for the interrupted secondary users in cognitive radio networks. *Annals of Operations Research*, *323*(1), 247-286. https://doi.org/10.1007/s10479-022-05160-x

[6] Pazouki, I., Soltani, R., & Lari, M. (2023). Wireless-Powered Communication Assisted by Two-Way Relay with Interference Alignment Underlaying Cognitive Radio Network. *Wireless Personal Communications*, *132*(2), 889-908. https://doi.org/10.1007/s11277-023-10641-8

[7] Onthoni, D. D., Sahoo, P. K., & Atiquzzaman, M. (2022). ASAA: Multihop and multiuser channel hopping protocols for cognitive-radio-enabled Internet of Things. *IEEE Internet of Things Journal*, *10*(9), 8305-8318. https://doi.org/10.1109/JIOT.2022.3230702

[8] Mughal, M. A., Ullah, A., Cheema, M. A. Z., Yu, X., & Jhanjhi, N. Z. (2024). An intelligent channel assignment algorithm for cognitive radio networks using a tree-centric approach in IoT. *Alexandria Engineering Journal*, *91*, 152-160. https://doi.org/10.1016/j.aej.2024.01.07

[9] Alqahtani, A. S., Changalasetty, S. B., Parthasarathy, P., Thota, L. S., & Mubarakali, A. (2023). Effective spectrum sensing using cognitive radios in 5G and wireless body area networks. *Computers and Electrical Engineering*, *105*, 108493. https://doi.org/10.1016/j.compeleceng.2022.108493

[10] Sethi, S. K. & Mahapatro, A. (2024). A Deep Learning-Based Discrete-Time Markov Chain Analysis of Cognitive Radio Network for Sustainable Internet of Things in 5G-Enabled Smart City. *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, *48*(1), 37-64. https://doi.org/10.1007/s40998-023-00665-y

[11] Salih, Q. M., Rahman, M. A., Asyhari, A. T., Naeem, M. K., Patwary, M., Alturki, R., & Ikram, M. A. (2023). Dynamic channel estimation-aware routing protocol in mobile cognitive radio networks for smart IIoT applications. *Digital Communications and Networks*, *9*(2), 367-382. https://doi.org/10.1016/j.dcan.2023.01.019

[12] Musa, A., Salameh, H. B., Halloush, R., Bataineh, R., & Qasaymeh, M. M. (2024). Variable rate power-controlled batch-based channel assignment for enhanced throughput in cognitive radio networks. *International Journal of Intelligent Networks*, *5*, 175-183. https://doi.org/10.1016/j.ijin.2024.04.001

[13] De Broglie, G., Morge-Rollet, L., Le Jeune, D., Le Roy, F., Roland, C., Canaff, C., & Diguet, J. P. (2024). New LTE-A Low-Latency Detectors for Cognitive Radio on Low-Cost FPGA. SoC. *Journal of Signal Processing Systems*, 1-15. https://doi.org/10.1007/s11265-024-01932-9

[14] Priyadarshi, R., Kumar, R. R., & Ying, Z. (2024). Techniques employed in distributedcognitive radio networks: a survey on routing intelligence. *Multimedia Tools and Applications*, 1-52. https://doi.org/10.1007/s11042-024-19054-6

[15] Manco, J. & Dayoub, I. (2024). Experimental assessment of spectrum sensing under time-varying channels for cognitive radio. *IEEE Sensors Letters*, *8*(8). https://doi.org/10.1109/LSENS.2024.3432738

[16] Bagadi, K., Abrao, T., & Benedetto, F. (2024). A novel machine learning approach for intelligent spectrum management in cognitive radio networks. *IEEE Networking Letters*, *5*(4). https://doi.org/10.1109/LNET.2023.3300274

[17] Mondal, S., Dutta, M. P., & Chakraborty, S. K. (2024). A hybrid deep learning based approach for spectrum sensing in cognitive radio. *Physical Communication*, *67*, 102497. https://doi.org/10.1016/j.phycom.2024.10249

[18] Balakumar, D. & Nandakumar, S. (2024). Blockchain-enabled cooperative spectrum sensing in 5G and B5G cognitive radio via massive multiple-input multiple-output nonorthogonal multiple access. *Results in Engineering*, *24*, 102840. https://doi.org/10.1016/j.rineng.2024.102840

[19] Tang, M., Zhu, W., Sun, S., & Xin, Y. (2023). Mathematical modeling of resource allocation for cognitive radio sensor health monitoring system using coevolutionary quantum-behaved particle swarm optimization. *Expert Systems with Applications*, *228*, 120388. https://doi.org/10.1016/j.eswa.2023.120388

[20] Srivastava, V., Singh, P., Mahajan, S., Pandit, A. K., Alshamrani, A. M., & Abouhawwash, M. (2023). Performance enhancement in clustering cooperative spectrum sensing for cognitive radio network using metaheuristic algorithm. *Scientific Reports*, *13*(1), 16827. https://doi.org/10.1038/s41598-023-44032-7

[21] Gopalan, S. H., Parvez, M. M., Manikandan, A., & Ramalingam, S. (2024). Cognitive radio spectrum allocation using Nash equilibrium with multiple scheduling resource selection algorithm. *Ain Shams Engineering Journal*, *15*(5), 102688. https://doi.org/10.1016/j.asej.2024.102688

[22] Saranya, S. & Jayarajan, P. (2024). Enhanced deep learning-based optimization model for the optimal energy efficiency-oriented Cognitive Radio Networks. *Ain Shams Engineering Journal*, 103051. https://doi.org/10.1016/j.asej.2024.103051

Contact information:

VIJAYAKUMAR K., Research Scholar
Department of Electronics and Communication Engineering,
Government College of Engineering,
Dharmapuri, Tamilnadu, India
E-mail: vijaya.gct@gmail.com

SUMATHY V., Professor
Department of Electronics and Communication Engineering,
Government College of Engineering,
Dharmapuri, Tamilnadu, India
E-mail: drsumathy@gct.ac.in